

Enhancing Self-Driving Car Performance: The Potential Dangers of AVs and Motorcycles

1st Given Edward Patch

Software Engineering and Artificial Intelligence (of MSc Year 4)

Application of Machine Learning

University of Wales Trinity St. Davids

Swansea, Wales

Student ID: 1801492

Abstract—Fully Autonomous Vehicles and their interaction with motorcycles are rarely considered. With the push of fully autonomous vehicles, ethical concern about motorcycles has risen. Primarily when countries with a higher population of motorcycles are targeted, this research proposal addresses the potential dangers of Autonomous Vehicles and motorcycles with the ‘Are Autonomous Vehicles a danger to motorcycles?’ research question. This research proposal aims to fill in the research gap of Autonomous Vehicles and motorcycle safety. The research looks into current object classification methods to understand the current problems and discover any potential solutions, theories or issues that manufacturers, motorcycle safety advocates and Government agencies can consider when it comes to awareness or development. The research methodology has two sections, primary and secondary. Primary: Statistical and Qualitative methodologies, and Secondary: Fundamental and Quantitative methods. Findings within this report: Vision-based AVs are valued over safety; Ultrasonic sensors are considered expensive, and other solutions can make the vehicle unattractive to the consumer market. The research question has three hypotheses statements to be determined within the research project:- ‘Motorcycles have blindspots that are often overlooked by human drivers, which AVs can detect and avoid.’, ‘In low light conditions, AVs may struggle to accurately detect and identify motorcycles, leading to potential safety issues on the road.’ and ‘Poor weather conditions, such as heavy rain, snow, or fog, can make it difficult for AVs to detect and react to motorcycles, increasing the risk of accidents.’.

Index Terms—Image Classification, Motorcycles, Autonomous Vehicles.

I. INTRODUCTION

AV cars are set to roll out in the UK by 2025, promising to release new laws and create thousands of jobs in the industry. The ideology of Autonomous EV cars aspires to improve safety, increase efficiency and change how individuals travel. Despite the remarkable advancements in Autonomous EV technology, challenges remain that need to be addressed to ensure the seamless integration of these vehicles on our roads. One life-death scenario challenge that still exists, however, has been reported by Autonomous companies is the inaccuracy of classification and interaction of self-driving cars with various road users, particularly motorcycles.

The main focus audience for this research project is Autonomous Vehicle (AV) manufacturers, motorcycle safety advocates and Government agencies responsible for regulating

AVs. The target audience is crucial to meet to advance the research and understanding of how to make roads safer around all types of vehicles. The dissertation will help forward experimental and thought process for future work towards these research groups. Any findings, results, discussions and conclusions will help identify the current issues and potential adaptations to integrate safety. AV manufacturers can use any findings, techniques and results mentioned in the report to determine any potential safety features to increase road safety. Motorcycle safety advocates can use any findings and discussions to support motorcycle trainers to devise awareness and safety around AVs and teach motorcyclists safety tips and maneuvers preventing any fatalities. Finally, the Government agencies can develop legal strategies to help AV manufacturers to take in consideration of any safety issues found within this research, making motorways and dual-carriageways safer around motorcycles.

Some key areas of the proposal include the reliability of AVs motorcycle detection within a lane. The way AVs interact with motorcycles in different situations, whether it is lane changes or merging, taking in considering of weather and visibility conditions. The potential risks for motorcycles and how to mitigate the risk of AV motorcycles.

The blog by Dolf Willigers, published by BMF [1] in 2012, ‘Autopilot Still Kills Motorcyclists’ provides a generalisation of the current issues and worries British motorcyclists deal with when coming to the idea of Fully and Lane Assisted Autonomous EVs. An idea that is raised in the article, ‘In both situations, the motorcycles, riding in the dark...’. This statement already raises the known problem of motorcycles being hard to see at night; hence, the drive for development with Hi-Vis reflection clothing, helmets and ‘always on’ dip beam laws. Although, an interesting problem that could be happening here is that the Image Classification algorithm implemented identifies motorcycle lights as street lights, street reflections (indicating danger), or cyclist/pedestrian bright lights that can aim directly into the vehicle’s lane. Usually, small things like this can blind a standard driver driving at night.

Figures (1, 2) visualises some of the potential impacts AVs may deal with. The diagram sourced from [2], illustrated by [3] demonstrates a potential problem, where if the AV misjudges the upcoming lane merge, and fails to detect motorcycle

within any potential blindspots could involve in fatalities with multiple road users. It is important to understand why systems may break down, especially when drivers behind the AV may not be active and paying attention.

The company, Tesla announces in 2021 that the company would remove a sensor called Ultrasonic Sensors, replacing the sensor with ‘Tesla Vision’ by 2022. Within this time, motorcycle incidents were rising with Tesla vehicles, including motorcycle fatalities. Rather than suggesting going back to Ultrasonic Sensor. Henceforth the importance of understanding object classification’s problems when identifying motorcycles.

These hypothesis statements assist the explore the research question, ‘Are AVs a Danger to Motorcycles?’:

- 1) Motorcycles have blindspots that are often overlooked by human drivers, which AVs can detect and avoid.
- 2) In low light conditions, AVs may struggle to accurately detect and identify motorcycles, leading to potential safety issues on the road.
- 3) Poor weather conditions, such as heavy rain, snow, or fog, can make it difficult for AVs to detect and react to motorcycles, increasing the risk of accidents.

**Lane change manoeuvre
of a self-driving car**

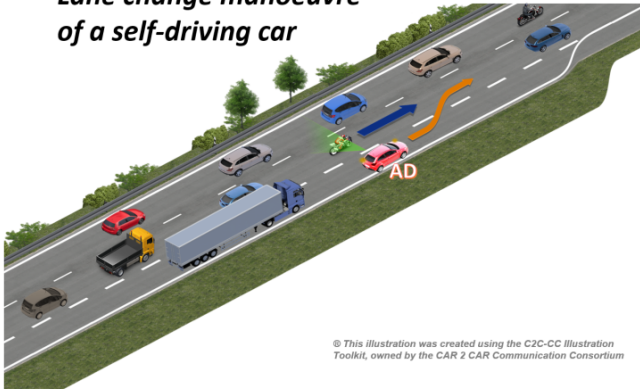


Fig. 1. C2C’s Illustration of Car Changing Lanes: Representation shows that a AV may misjudge the speed of the other vehicle with limited visibility. [2]

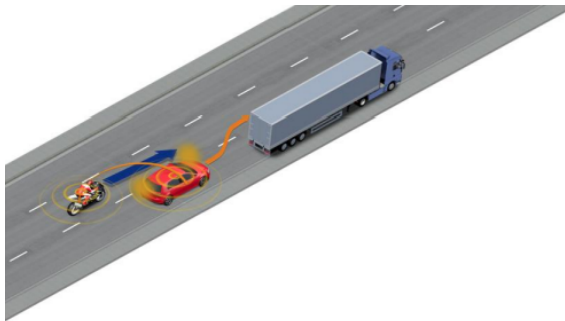


Fig. 2. C2C’s Illustration of Motorcycle within Car’s Blindspot: Representation displays that a AV could pull out, not detecting the motorcycle. [4]

II. LITERATURE REVIEW

Firstly, it is essential to understand how vision works on AV and what techniques are in place to allow vehicles to function correctly and safely. Journal Article, ‘AVs: from paradigms to technology’, authored by Silviu Ionita [5], offers underlying information about the foundation of autonomous vehicle systems. It is equally important to understand how motorcycles function within traffic and understand the reasoning behind motorcyclist mentality.

Motorcycle filtering and some of the law insights behind the concept. Australia and USA states have different definitions of filtering. Some states declare filtering legal where other states declare filtering illegal. Thailand country made filtering illegal, however, some of these states or countries where filtering is illegal are poorly policed, indicating that motorcyclists may filter if an opportunity arises. That means AV vehicles should anticipate filtering even in countries/states where filtering is illegal to minimize the number of casualties and incidents. [6]

An ‘intelligent vehicles’ paradigm has three logical rule statements to follow. Firstly, the system will collect data from the driver, developing the knowledge from itself and the driver. Second, the system will have to perform some judgement. Silviu Ionita [5] mentions that it is paramount to filter the data through logical statements and apply multivalent logic to handle uncertainty better, creating a better judgement. ADAS require consistent autonomous behaviour to collect and handle the data even when the system is not in control. This behaviour means that the developers can collect data on what the system would have done if it were in control, allowing any refinement down the line and enabling AVs to work more efficiently.

Figure 3 provides the structure of Advanced Driver Assistance Systems (ADAS) functions linking the responsibilities to the decision and action. Strategic Processes are near real-time, Tactical Processes are real-time, and Direct are short as possible. These three functionalities are fundamental when understanding how an ADAS vehicle copes and how an AV will tend to handle situations. [5] It is necessary to establish that the AV will only rely on its judgement after the decision to remove human interaction. Some of these system paradigms reflects on the capabilities of AVs involving blindspots, low-light and poor weather conditions.

Process Level	Decision	Action	Function
Strategic	AI Models	Near real time	- Trip/route planning - Route optimization and selection - Route reconfiguration
Tactical	AI Models & Adaptive models	Real time	- Maneuver planning, including control of: steering, speed, distance, acceleration/ deceleration - All types of current perceptions and events anticipated in the environment
Direct	Error-based	Reflex (as short as possible)	- Breaking - All types of current events sensed in the environment

Fig. 3. Classes of ADAS and their Requirements for Decision and Execution [5]

Finding the suitable dataset for the given research question involves first identifying the required information. The requirements of the dataset need to have motorcycles on the road

with different situations, camera angles and visibility. After exploring through some datasets, three image classification datasets, 'TuSimple' [7], 'Car vs Bike Classification' [8] and 'MB10000' [9]. The ideal datasets at the time was 'TuSimple'. However, the dataset was twenty-five gigabytes, and meant that training the dataset was too much for individual research. The 'Car vs Bike Classification' dataset lacked authentic motorcycle and car images in realistic situations. However, the dataset was lightweight, with one hundred and eight megabytes. These mentioned specifications meant that the 'MB10000' had an optimistic fitness to support this experiment. The dataset has realistic situations, motorcycles with other vehicles and image sequences to support image classification. The dataset has four-hundred and twenty-six megabytes of filesize.

When investigating how AVs handle blindspot handling compared to human drivers, the paper 'Automated driving: Safety blind spots' by Ian Y. Noy [10] suggests the current implementations within ADAS and compares it to standard driving errors. Although, the paper does not directly reflect on motorcycles, the paper details ADAS systems and how the transition from ADAS to AVs is possible. An important quote from the paper is that 'AD technologies are suboptimal in that they fail to address critical blind spots and will likely lead to unnecessary losses and injuries because insufficient consideration is given to integrating the human element into overall sociotechnical road transportation system' [10] suggests that transitioning from ADAS to AVs is relatively dangerous if blindspot judgements are overlooked. With further research in this area, it will provide more information to understand if AVs are safer than human drivers on the road.

'Pedestrian, Bike, Motorcycle and Vehicle Classification via Deep Learning: Deep Belief Network and Small Training Set' by Yen-Yi Wu [11] goes over different visibility levels that affect pedestrians, bikes, motorcycles and vehicles and how image classification affects these vehicles. The image preprocessing involves converting colour images to greyscale. Including edge emphasis, detection to enhance to the image, with the fundamental aim to detect edges of objects seamlessly. The paper suggests using a fixed threshold and Otsu methods to threshold greyscale images and use bilinear interpolation for image resizing. These methods should increase the visibility of the objects within the images are good notes for when conducting any experiments.

As most AVs use object classification, so it is a good idea to explore some of the different techniques available for image classification for real world applications. 'Detection and classification of vehicles for traffic video analytics' writing by Ahmad Arinaldi [12] recommends R-CNN (Region-based Convolutional Neural Network) to process video frames (images) for object classification. The data preprocessing and object classification Ahmad Arinaldi [12] provides, offers a solution for moving vehicles in traffic vehicles. The paper covers both Mixture of Gaussian (MoG) to remove the background and Support Vector Machine (SVM) testing it against Ahmad Arinaldi's [12] 'Faster R-CNN' Neural Network, which is ideal for the problem when it comes to detection

and classification of vehicles in moving traffic scenarios. The Indonesian Toll Road dataset scored $.672 \pm .150$ ranging from 52.2% - 82.2% and MIT Traffic $.694 \pm .0013$ ranging from 68.1% to 70.7% accuracy.

Yen-Yi Wu [11] suggests the use of a Deep Belief Networks (DBN) model to use for object classification. The model works well to classify images: pedestrians, bikes, motorcycles and other vehicles. The model thrives a 89.53% accuracy.

R-CNN model merges a CNN approached model with Region-based model to create a deeper layered model. The aim is to increase accuracy and performance when it comes to object classification. The R-CNN uses a selective search algorithm to find certain features within the set of images, and focus on the objects that match the specified features using a diverse of strategies. This approach aims means that when training the model, it is equally important to understand what the layers do and how they filter the image to change the test data to analyse the difference performance and accuracies of the training and testing. [13] [14]

DBN model is based off Restricted Boltzmann Machine (RBM) layers to train the model. According to 'An overview on Restricted Boltzmann Machines' [15] explains that RBMs pre-train the weights of the networks. This is done layer by layer, and applies gradient descent methods to fine tune the weights. This alone allows the neural network to optimise the hyper-parameters, which in turn boosts accuracy and optimises the performance of the model overall.

Both model suggestions both use CNN, whether it is merging CNN or comparing to CNN. A layer used in the Journal Article, 'Detection of Motorcyclists without Helmet in Videos using Convolutional Neural Network' written by C. Vishnu [16] tests for motorcyclists wearing helmets and no helmets. The layers proposed by the author should benefit the datasets used in this research project. The layer structure appears to be faigue, although, involves relu, maxpooling, fully connected and a loss function (Support Vector Machines or Softmax) layers.

Figure 3 displays the DBN and RBM layers from the paper, 'Parallel computing method of deep belief networks and its application to traffic flow prediction' illustrated by Lu Zhao [17]. DBN is not a convolutional network, compared to CNN. DBN consists of a two-layer graph, including a visible layer below and a hidden layer above displayed in figure 4. The author and illustrator mentions that the RBM layers illustrated are slightly different to the classical Boltzmann Machine. [17]

III. METHODOLOGY

The project will involve the research, design, experiments and findings to answer the research question. The hypothesis statements will drive the development of the study and investigations to provide a statistical analysis of any potential safety issues.

A. Outline

The study will select relevant Machine Learning/Deep Learning (ML/DL) models, hyper-parameters and techniques,

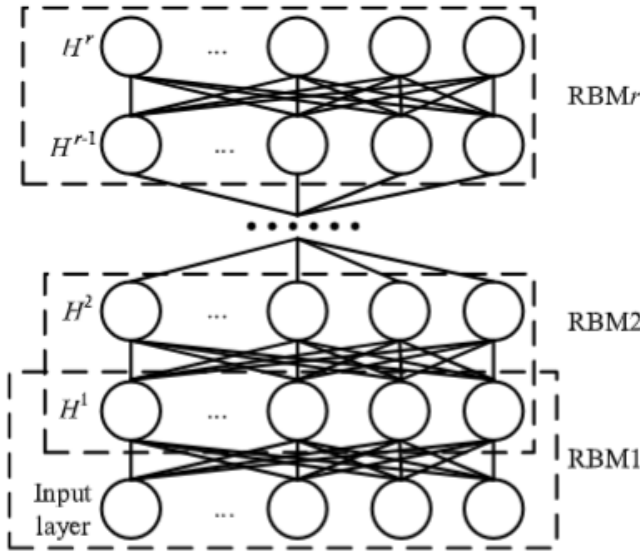


Fig. 1. Basic structure of a DBN.

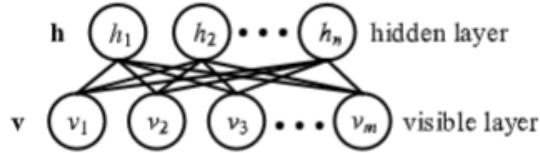


Fig. 2. Basic structure of an RBM.

Fig. 4. DBN and RBM Model Layers [17]

with some existing research to support the experimentation results. Some initial research papers and datasets are enclosed in this paper. However, if any new research developments are established during the experimentation, then consideration of the research would include in the research section that backs up the investigation. The study will uncover and cover some of the existing research. However, expand on any technicalities to help prove the established hypothesis statements.

B. Aim and Objectives

The aim of the study is to address the problems with AVs to fulfill the research gap. The problems have been addressed within conference papers and even when it comes to object classifications. Although, with the lowest of incidents, whether it is due to the safety training of motorcyclists or population that actually ride, dependent on the country, the problem is rarely addressed thoroughly. If AVs roll out into regions like Southeast Asia: Indonesia, Vietnam, Thailand and others, and European countries: Italy, Spain, Brazil and others, then the problem will appear more, not allowing organisations to brush the problem ‘under the rug’. The objective is to find some theoretical logic of the underlying problems and potential solutions or considerations for ADAS/AVs to adapt decreasing any potential tragic accidents.

C. Project Structure

The research during the project must justify tools to support image preprocessing, analysing and classification to provide an understanding of the problems taking place. Image preprocessing is a significant consideration in the project to answer all the hypotheses, as motorcycles may be in a blind spot, but with better adjustments, the image classification could see blur or shadows easier with sharper settings or if the time and weather have poor visibility, then dangerous the image to greyscale, and increasing edge sharpness could help make the motorcycle outline more clear. Different classification methods can improve the accuracy of a data model, including using various layers, hyper-parameters, and techniques during the training of a dataset.

The experiment would look into image classification with the selected dataset providing information on possible misclassifications from the chosen dataset. The image classification structure would follow some standards that AVs use. However, AVs would use object classification libraries that support real-time footage. Image classification aims to see how motorcycles are identified among other vehicles to extend the research.

Some of the strategies to determine the hypothesis statements is to select a model like DBN and CNN or R-CNN and to compare the results with the corresponding research results. Find image classification research papers for example, ‘An Analysis of Convolutional Neural Networks For Image Classification’ researched by Neha Sharma [18] demonstrates a good example of a CNN structure.

This AI project will involve seven phases in accordance with the paper ‘Developing ML/DL Models: A Design Framework’ authored by Meenu Mary John [19] involving Business Case Specification, Data Exploration, Feature Engineering, Experimentation, Development, Deployment and Operational. The Business Case Specification, in this case, is to find out if motorcycles are in danger around AVs and find suggestions or research pathways to answer the hypothesis that supports the research question thoroughly. It is essential to find datasets that support the business case specifications. During the data exploration phase, exploring some available datasets and filtering them out to better back the research question is essential.

Feature engineering takes place to determine the relevant data fields or features that benefit the study. For example, non-vehicle objects like traffic lights and pedestrians are not required if the focus is on motorcycles. Although, it can be equally argued that when AVs function, they process many objects simultaneously for better awareness.

The experimentation phase includes developing a model for the dataset, compiling the model and reviewing the data to optimise the model for the dataset. This experimentation will already shape potential issues with the dataset. Each time the data is run with different tunings, it will help develop an idea of the potential issues with the dataset.

The development phase is where findings from the experimentation are presented. This phase will formalise the results and suggest to the target audience the project’s future work.

The Deployment and Operational phases are not required. However, a replacement of a Review phase may be where results and findings can be discussed, and any suggestions to optimise the experimentations for future work.

D. Evaluation Metrics

During the experimentation, it is necessary to discuss of how the analyst of experimental data may take place. This information will guide the project with relevant data backing up the optimisation and accuracy during the ML prototyping, and gathering feedback for the research question to present the findings and develop any potential solutions or future work.

Two common methods of observing performance and accuracy among the different classes available within a dataset is Confusion Matrices and Classification Reports. These tools provide a clear indication of overfitting, underfitting and accuracy. The confusion matrix does this by demonstrating true positives and false positives, which the main focus to back up the research question would be the Motorcycle feature to see where any false positives are detected. The Classification Report displays a range of information involving 'Precision', 'Recall', 'F1-Score' and 'Support' of each features; detailing any potential issues of outliers. Three averages: 'Accuracy', 'Macro Avg' and 'Weighted Avg.' are included to show the overall accuracy of the model. [20] [21]

As Neural Networks train with a given epoch, meaning how many iterations the test data would go through training. A history of these iterations will be on record and displayed on a 'Validation and Training Loss' graph to indicate the loss gap of the initial learning and the fitness of the trained and validation data to indicate the performance and any potential improvements, [21]

E. Development Methodology

Due to the nature of the AI project, the Agile development methodology does not fit. Although, if the project involves a team of developers, then the Agile development methodology will make the better fit. The AI project has a small team and requires a lot of repetition to find the best fit and results for the experimentation. The Iterative development methodology is the best approach. The Agile Methodology could cost anywhere from £422.91 (Freelancer Team Members) to £2085.04 (Payroll Team Members) [22]

Where usually, Agile development methodology has an initial cost factor, and the development saves coordination, flexibility and performance within a team development environment. However, it does not fit in a project that aims to deliver results to address a safety issue. The Agile methodologies, Iterative and Rapid Application Development (RAD) development methodologies address this project better, with the ability to make a prototype model, test and refine it.

RAD is a risky methodology as it does not allow the flexibility to redesign the plans to enable definition when addressing the given safety concern. Therefore, the Iteration development model is an ideal solution, allowing the ability of initial planning and then additional planning and requirement

changes, also continuously updating the analysis and design, testing and evaluation. This key methodology cycle will benefit the ideology of setting the layers up and evaluating the results. Agile Methodology also uses User Stories, which is excellent if a platform is being made. However, the user stories would get repetitive during the research project, which wastes time in this specific scenario.

F. Ethical Impacts

AVs on the road pose ethical implications, especially concerning interaction with other road users focusing on motorcycles. These ethical implications impact safety, privacy and security concerns. AVs are not ADAS and have no override system for passengers, making this a paramount moral concern.

AVs must ensure the safety of every road user, including motorcyclists. It is essential to ensure that AVs are not deployed onto roads in any country until enough research is conducted on motorcycles or even other road users, including cyclists and pedestrians. Organisations' goals are to focus on the vision side of AI usage, which means that implemented systems must achieve high results. Any performance or average issues could result in a significant accident. An ethical issue could be developed when AVs react to night-time driving around motorcycles, swerving or overtaking, mistaking the vehicle as a cyclist, and not giving the correct space. Furthermore, any blindspots of an AV or other aspects overlooked, like reaction times in terms of computational execution times, could result in catastrophic safety implications for motorcyclists.

A survey conducted by Rahman, Dey, Das and Sherfin-ski [23] studied by Kristen Pammer [24] suggests that 57% of pedestrians and cyclists felt 'safe or very safe' sharing with AVs. Kristen Pammer [24] conducted a survey and this was his statement:

"The survey findings were supported by a simple question at the end of the survey; 'If you have any other views on the increasing use of autonomous/self-drive cars, please provide them here' where a surprising 250 participants volunteered responses such as 'As an avid motorcyclist I actually trust a computer to see me better than most humans.'" [24]

The response shows the massive trust AVs will build, and the importance not to ignore the responsibilities that come with AVs. When road users become too comfortable around AVs being able to predict them, then humans may try to 'outsmart' them finding a potential issue that the developers appears to have overlooked on. This research project aims to provide information on how to handle the potential problems with AVs.

G. Roles

The following roles are required to carry out this project involves a project manager, researcher, data scientist, software developer, motorcycle safety expert, AV engineer, product sponsor and stakeholders.

A Project manager is in charge of making sure of the flow of the ongoing tasks. They are in charge of setting deadlines, providing milestones and assigning tasks to the team. A project without a project developer, would slow down development significantly.

A Researcher carries out any research activities including collecting, analysing and interpreting data, and preparing research reports.

A ML engineer/Software Developer could be considered when it comes to the prototype of the AI system, involving the implementation of the Neural Network, and any other software infrastructure that is required. For example, if extra software is required to support the experimentation better.

Consideration of both Motorcycle Safety expert and AV engineering to gather inside information to formulate a credible research project.

Project Sponser to provide funding to support the research project including resources for the project.

Stakeholders are responsible to provide feedback and input within the project, keeping the project outcomes aligned to the needs and expectations.

H. Project Management

The project management tool for this project requires GitHub Project, and the source control to manage the project is Git. Using a Kaban and Gantt Chart allows the team to maintain an organised structure when executing tasks to complete Milestones and iterations. The iterative development approach required some setting up, so on GitHub Project, six iterations exist, with two being contingency.

Project Link: <https://github.com/users/ShinkuKira21/projects/2/views/4>

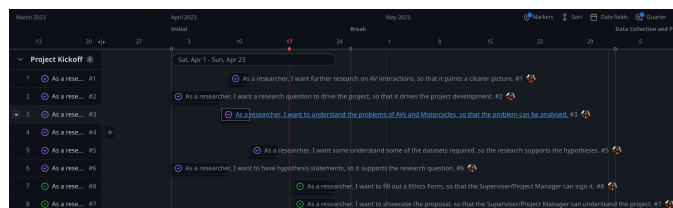


Fig. 5. Kaban Chart: Project Management

Figure 6 shows the project plan for the proposal phase, milestone: 'Project Kickoff'. The milestone appears to have a schedule of April 1 to April 23. The focus areas involve choosing appropriate research with the relevant hypotheses, fundamental research of AVs and motorcycles to understand current issues with the architecture in place, research to understand AV interactions and research containing appropriate datasets needed to support the hypotheses. This stage requires seven tasks to complete, with some fading into others to complete. The idea of phasing into another assignment is because some tasks help achieve the latter.

Also, the milestone has two open tasks assigned to the researcher. These tasks involve communicating with the Project Manager/Supervisor to propose the project idea and filling out

an ethical form so the supervisor can sign it. The other tasks display completed tasks.

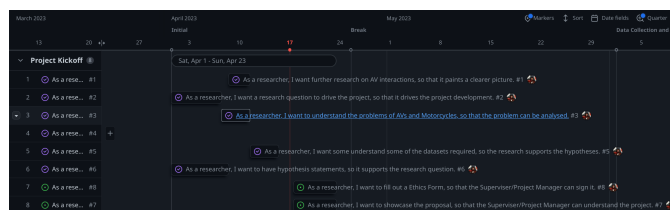


Fig. 6. Schedule of Milestone: Project Kickoff

Figure 7, milestone 'Data Collection and Preparation', involves six tasks from June 2 to June 14. The tasks are green, meaning that the tasks are still open. Each task should take up to 2 days to complete. The following requirements involved with the tasks are as described:

- Identify relevant data sources.
- Review and select Appropriate datasets.
- Clean and preprocess the data.
- Explore and visualise the data.
- Transform the data into a suitable format for the analysis.
- Document the data collection and preparation methods.

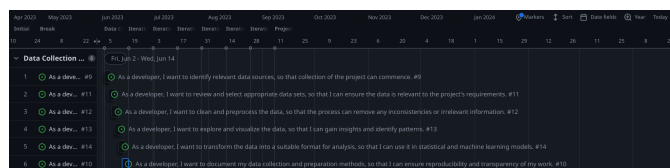


Fig. 7. Schedule of Milestone: Data Collection and Preparation

Figures (8 9 10 11) show four milestones. Notice how the figure captions now say 'Iteration Milestone' because these are not standard milestones. These milestones are templated to be broken down and repeated for each iteration incrementation. Each iteration has a time box of two weeks and four phases, research and planning, model development and training, model testing and evaluation, and documentation and discussion. Every time an iteration completes, the next iteration will either have tasks from the backlog, uncompleted tasks from the previous iteration, or new tasks for each phase of the iteration based on the last iteration's 'Discussion and Documentation' phase.

The first element of the iteration is about research and planning. The 'Research and Planning' part of the initial iteration starts on June 16 to June 19, with two tasks, gathering and analysing potential dangers with AVs and reviewing and discussing findings with the team and Project Manager/Supervisor.

The 'Model Development and Training' section of the initial iteration involves the creation of the chosen model. The milestone lasts six days from June 20 to June 26, with two tasks, lasting three days each, developing and training the Neural Network models and monitoring the model development progress.



Fig. 8. Iteration Milestone: Research and Planning

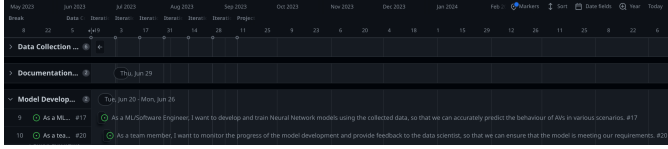


Fig. 9. Iteration Milestone: Model Development and Training

The ‘Model Testing and Evaluation’ section of the initial iteration has a timeline of June 26 to June 27, with two tasks taking a day to complete. The two tasks rely on each other and involve evaluating and testing the Neural Network and reviewing the model evaluation results.

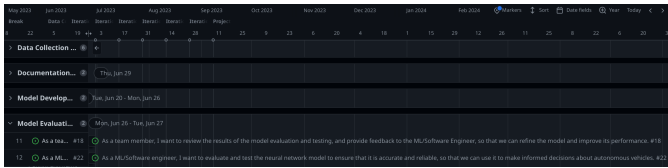


Fig. 10. Iteration Milestone: Model Testing and Evaluation

The ‘Discussion and Documentation’ section of the lasts for one day, the completion day is June 29. This milestone includes two tasks, documenting the research findings, and reviewing and edition of the documentation and reports.

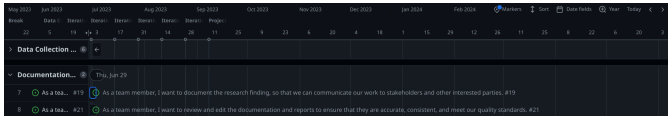


Fig. 11. Iteration Milestone: Discussion and Documentation

The milestone ‘Project Completion’ provides tasks to finalise the project. This milestone focuses on the closing argument of the project and concludes. The milestone commences from September 8 to September 21, with four tasks to complete. The first task, ‘reflect on the hypotheses’, needs one day to finish. The second task, ‘discuss any unexpected findings or outcomes from the project’, require two days to complete. The third task, ‘reflect on the lessons we learned during the project’, needs four days to complete. The fourth task, ‘evaluate the project’s overall success’, needs three days to complete.

IV. RESULT COLLECTION

Result collection is a collection of different techniques used within the project. These methodologies narrow down useful

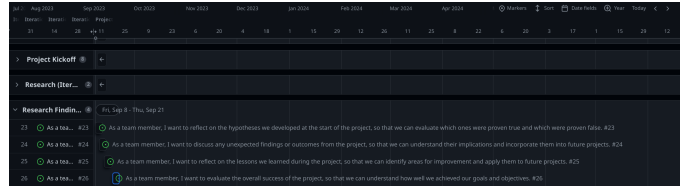


Fig. 12. Schedule of Milestone: Project Completion

information types to back up the project. As the research question seems to be very limited within the research area involving AVs/ADAS and motorcycles, it may be hard to narrow the research collection down. From the research conducted so far, the project follows on the lines of fundamental, statistical, quantitative and qualitative research. The main focus to answer the research question thoroughly would be statistical, quantitative research methods, whereas fundamental and qualitative research methods would act as a secondary focus to widen the research content, providing a better understanding of the research problem.

A. Fundamental Research

Fundamental research methodology builds a directive of a research area driven by curiosity. This type of research collection increases the understanding of a selected research topic, which is vital in cases where not many research papers exist. Fundamental research papers alone are not substantial to start developing towards a research project, as the name suggests, it creates a foundation and provides insights to understanding any problems found during the research study. These papers tend to cover basic understandings of phenomenon’s, which in turn backs up the research question. These research materials may include surveys, interviews, observations and experiments. [25]

In the context of AVs and motorcycles, the research methodology seeks to understand any underlying principles of the interaction of these vehicle types on the road. It may even contain discussions and analytics of crash data or theoretical requirements that AV organisations should follow. For example, a study of how drivers and rider perceive each other on the road would impact the research approach, taking in account of the AVs visibility requirements. For the project, consideration of conference papers, case studies and surveys should help form any research directives to approach the testing of the hypotheses statements.

B. Statistical Research

Statistical research is a critical component of this research project, as interpreting the analytical data generated from the Neural Network is important. AVs and ADAS are complex systems, and require a good understanding of the statistics of real life events to understand hypothetical situations. The goal of statistical research is to identify patterns, relationships and trends within the data. These three variables allow the testing about each individual hypothesis and forming the conclusions of the research method.

Statistical research could involve comparing other object classifications papers involved with AVs and motorcycles, taking account of the design plan, neural network model and layers, results and discussions to give an understanding of industry standard results. This also gives a great way to test the findings from the research project against the statistical findings and then form a detailed report of the findings, and provide a useful further work section. Statistical research has been demonstrated to make sure that the datasets are relevant and up-to-date Use Cases, and to understand the initial problems with motorcycles and ADAS/AVs to develop the research question.

C. Quantitative Research

Quantitative research involves the numerical data to collect and analyse data. This has a secondary importance similarly to the fundamental research methodology. This research collection appears a few times whether it is working with the algorithm, Confusion Matrix or understanding numerical data gathered from fundamental and statistical research papers to understand of variables in relation of AVs and motorcycles. Quantitative research methodology can help with identifying and aids with developing evidence-based recommendations for improving motorcycle safety.

Quantitative research methodology tends to involve surveys, questionnaires and user studies. The methods enable the research to contain a large amounts of numerical data related to the research question. Numerical techniques can also provide tools to conduct correlation analysis and hypothesis testing, in accordance with research from the statistical side and experimental results. The quantitative methods has been applied to check performance, size and other key factors when it comes to preparing the Neural Network to make sure that the hypotheses are accurate and workable.

D. Qualitative Research

Qualitative research is a crucial factor of this project. As seen in this proposal, datasets had to be observed to make sure they could withstand the hypotheses. During the prototyping and evaluating of the model, observations will be made and cross-referenced to make sure that the findings are accurate. This type of testing could help work out any potential issues with current data structures or even provide some awareness of problems that may have not been considered before. It is also important to make notes from other research projects with qualitative research to consider any key points.

In addition, observation studies could help enhance the research development. This could be finding case studies that provide videos of AVs in process with descriptions of what the program is doing and what systems are in place. This content could involve indepth interviews with experts and stakeholders to understand AVs and motorcycle's current interactions and known concerns. It could also be a useful tool communicating to some motorcycle instructors or experts to understand if there is any on-going issues with ADAS vehicles and motorcycles.

These could aid the study further in seeing or hearing the experiences.

V. EVALUATION

The research question, 'Are AVs a Danger to Motorcycles?', involves three hypotheses: 'Motorcycles have blindspots that are often overlooked by human drivers, which AVs can detect and avoid.', 'In low light conditions, AVs may struggle to accurately detect and identify motorcycles, leading to potential safety issues on the road' and 'Poor weather conditions, such as heavy rain, snow, or fog, can make it difficult for AVs to detect and react to motorcycles, increasing the risk of accidents' have been observed and considered throughout the proposal. The project's target audience should aim towards AV manufacturers, motorcycle safety advocates and Government agencies, as it addresses an overlooked ethical issue.

The literature review ensures methods that can provide research support to aid each hypothesis. The methodology considers the critical areas of the research project, including the research, project infrastructure, development methodologies, project management and project costs. The refined project uses the literature review to create an affordable, time-critical, practical project supporting the research question. The research collection methods focus on two primary methodologies, statistical and quantitative and two secondary methodologies to support the primary research collection methods. DL algorithms use some of the mentioned research collections in the natural developmental form. It was found that with the research gap directly at AVs and motorcycles, limiting the research collection too much would make the research project less likely to provide the necessary research development.

Several metrics are used to evaluate the success of the project and to formalise the result of the project:

- 1) The accuracy of the DL algorithm in detecting motorcycles in different situations should be measured and compared to selected research papers to keep up with industry standards.
- 2) The performance and accuracy of the DL algorithm will be observed and put into consideration how accidents may occur in different situations.
- 3) Real-life situations should be collected from verified sources or interviews with instructors to understand if they have had any issues with learners around ADAS vehicles in the UK to provide real-world situation support.

In conclusion, the project addresses the ethical issue with AVs's interaction with motorcycles. The project is designed to address the issue and provide insight into any problems that Object Classifications currently have detecting motorcycles in different situations. The project's future work is to provide clarity and considerations of safety implications, implementations or possibilities.

VI. TERMINOLOGY

List of terminologies used in this document:-

- AV: Automonous Vehicles.

- ADAS: Advanced Driver Assistance Systems.
- ML/DL: Machine Learning and Deep Learning.
- MoG: Mixture of Gaussian.
- SVM: Support Vector Machines.

VII. REFERENCE LIST

- [1] Dolf Willigers, "Autopilot still kills motorcyclists – British Motorcyclists Federation," Sep. 2022. [Online]. Available: <https://www.britishmotorcyclists.co.uk/autopilot-still-kills-motorcyclists/>
- [2] aecm | The Motorcycle Industry in Europe, "Looking into the future: connected, cooperative and automated mobility," in *ACEM*. [Online]. Available: <https://roadsafetystrategy.acem.eu/home/looking-into-the-future-connected-cooperative-and-automated-mobility/>
- [3] Connected Motorcycle Consortium, "Applications to improve rider safety." [Online]. Available: <https://www.cmc-info.net/applications.html>
- [4] —, "Application Specification | Chapter: Lane Change Warning / Blind Spot Warning (LCW/BSW)." Connected Motorcycle Consortium, Nov. 2020. [Online]. Available: https://www.cmc-info.net/uploads/1/2/1/4/121453783/3.3_-_lcw-bsw_-_use_case_description__technical_description.pdf
- [5] S. Ionita, "Autonomous vehicles: from paradigms to technology," *IOP Conference Series: Materials Science and Engineering*, vol. 252, no. 1, p. 012098, Oct. 2017, publisher: IOP Publishing. [Online]. Available: <https://dx.doi.org/10.1088/1757-899X/252/1/012098>
- [6] T. Promraksa, T. Satiennam, W. Satiennam, and N. Kronprasert, "Lane-Filtering Behavior of Motorcycle Riders at Signalized Urban Intersections," *Journal of Advanced Transportation*, vol. 2022, p. e5662117, Aug. 2022, publisher: Hindawi. [Online]. Available: <https://www.hindawi.com/journals/jat/2022/5662117/>
- [7] S.-G. Jeong, J. Kim, S. Kim, and J. Min, "End-to-end learning of image based lane-change decision," in *2017 IEEE Intelligent Vehicles Symposium (IV)*, Jun. 2017, pp. 1602–1607.
- [8] Deepnets, "Car vs Bike Classification Dataset." [Online]. Available: <https://www.kaggle.com/datasets/utkarshsaxenadn/car-vs-bike-classification-dataset>
- [9] J. E. Espinosa, S. A. Velastin, and J. W. Branch, "Motorcycle detection and classification in urban Scenarios using a model based on Faster R-CNN," *arXiv:1808.02299 [cs]*, Aug. 2018. [Online]. Available: <http://arxiv.org/abs/1808.02299>
- [10] I. Y. Noy, D. Shinar, and W. J. Horrey, "Automated driving: Safety blind spots," *Safety Science*, vol. 102, pp. 68–78, 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0925753517304198>
- [11] Y.-Y. Wu and C.-M. Tsai, "Pedestrian, bike, motorcycle, and vehicle classification via deep learning: Deep belief network and small training set," in *2016 International Conference on Applied System Innovation (ICASI)*, May 2016, pp. 1–4.
- [12] A. Arinaldi, J. A. Pradana, and A. A. Gurusinga, "Detection and classification of vehicles for traffic video analytics," *INNS Conference on Big Data and Deep Learning*, vol. 144, pp. 259–268, Jan. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1877050918322361>
- [13] J. R. R. Uijlings, K. E. A. van de Sande, T. Gevers, and A. W. M. Smeulders, "Selective Search for Object Recognition," *International Journal of Computer Vision*, vol. 104, no. 2, pp. 154–171, Sep. 2013. [Online]. Available: <https://doi.org/10.1007/s11263-013-0620-5>
- [14] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in *Advances in Neural Information Processing Systems*, C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, Eds., vol. 28. Curran Associates, Inc., 2015. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2015/file/14bfa6bb14875e45bba028a21ed38046-Paper.pdf
- [15] N. Zhang, S. Ding, J. Zhang, and Y. Xue, "An overview on Restricted Boltzmann Machines," *Neurocomputing*, vol. 275, pp. 1186–1199, Jan. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0925231217315849>
- [16] C. Vishnu, D. Singh, C. K. Mohan, and S. Babu, "Detection of motorcyclists without helmet in videos using convolutional neural network," in *2017 International Joint Conference on Neural Networks (IJCNN)*, May 2017, pp. 3036–3041, iSSN: 2161-4407.
- [17] L. Zhao, Y. Zhou, H. Lu, and H. Fujita, "Parallel computing method of deep belief networks and its application to traffic flow prediction," *Knowledge-Based Systems*, vol. 163, pp. 972–987, Jan. 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0950705118305112>
- [18] N. Sharma, V. Jain, and A. Mishra, "An Analysis Of Convolutional Neural Networks For Image Classification," *International Conference on Computational Intelligence and Data Science*, vol. 132, pp. 377–384, Jan. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1877050918309335>
- [19] M. M. John, H. H. Olsson, and J. Bosch, "Developing ML/DL Models: A Design Framework," in *Proceedings of the International Conference on Software and System Processes*, ser. ICSSP '20. New York, NY, USA: Association for Computing Machinery, 2020, pp. 1–10, event-place: Seoul, Republic of Korea. [Online]. Available: <https://doi.org/10.1145/3379177.3388892>
- [20] J. Liang, "Confusion Matrix: Machine Learning," *POGIL Activity Clearinghouse*, vol. 3, no. 4, Dec. 2022, number: 4. [Online]. Available: <https://pac.pogil.org/index.php/pac/article/view/304>
- [21] S. Panigrahi, A. Nanda, and T. Swarnkar, "Deep Learning Approach for Image Classification," in *2018 2nd International Conference on Data Science and Business Analytics (ICDSBA)*, Sep. 2018, pp. 511–516.
- [22] M. Owais and R. Ramakishore, "Effort, duration and cost estimation in agile software development," in *2016 Ninth International Conference on Contemporary Computing (IC3)*, 2016, pp. 1–5.
- [23] Rahman, Dey, and Sherfinski, "AV Survey Results 2017," 2017. [Online]. Available: <https://bikepgh.org/our-work/advocacy/save/survey/>
- [24] K. Pammer, H. Predojevic, and A. McKerral, "Humans vs. machines; motorcyclists and car drivers differ in their opinion and trust of self-drive vehicles," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 92, pp. 143–154, Jan. 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1369847822002807>
- [25] M. Saunders, P. Lewis, and A. Thornhill, *Research Methods for Business Students*, 6th ed. Pearson Education Limited, 2012.